DOCUMENT RESUME

ED 422 389 TM 028 951

AUTHOR	Thompson, Bruce
TITLE	Using Q-Technique Factor Analysis in Education Program Evaluations or Research: An Introductory Primer.
PUB DATE	1998-05-02
NOTE	39p.; Paper presented at the Annual Conference on Research Innovations in Early Intervention (Charleston, SC, May 2, 1998).
PUB TYPE	Reports - Descriptive (141) -- Speeches/Meeting Papers (150)
EDRS PRICE	MF01/PC02 Plus Postage.
DESCRIPTORS	Computer Software; *Factor Analysis; Heuristics; Identification; *Personality Assessment; *Q Methodology; Tables (Data)

ABSTRACT

This paper explains how Q-technique factor analysis can be used to identify types or clusters of people with similar views. Q-technique factor analysis can be implemented with commonly available statistical software such as the Statistical Package for the Social Sciences (SPSS). The paper addresses three questions: (1) How many types (factors) of people are there?; (2) Are the expected people most associated with the expected person factors?; and (3) Which variables were and were not useful in differentiating the various person types/factors? The Q-technique methods described are well suited to studying education phenomena in which there are numerous ideals present in a reality in which only a limited number of ends or means can be realistically pursued. The use of Q-technique factor analysis is concretely illustrated using a heuristic data set involving a hypothetical investigation of parent and teacher perceptions of special education programs. An appendix contains the SPSS program to analyze data from the first table. (Contains 8 tables, 3 figures, and 30 references.) (Author/SLD)

qtech.wp1 4/24/98

Using Q-technique Factor Analysis in Education Program Evaluations or Research: An Introductory Primer

Bruce Thompson

Texas A&M University 77843-4225
and
Baylor College of Medicine

Paper presented at the annual Conference on Research Innovations in Early Intervention (CRIEI), Charleston, SC, May 2, 1998. The author and related reprints can be accessed on the Internet through Web address: **"http//acs.tamu.edu/~bbt6147/"**.

ABSTRACT

The present paper explains how a particular kind of factor analysis--Q-technique factor analysis--can be used to identify types or clusters of people with similar views. Q-technique factor analysis can be implemented with commonly available statistical software (e.g., SPSS), and addresses three questions:

1. How many types (factors) of people are there?
2. Are the expected people most associated with the expected person factors?
3. Which variables were and were not useful in differentiating the various person types/factors?

The Q-technique methods described here are well suited to studying education phenomenon in which there are numerous ideals present in a reality in which only a limited number of ends or means can be realistically pursued. The use of Q-technique factor analysis is concretely illustrated using a heuristic data set involving a hypothetical investigation of parent and teacher perceptions of special education programs.

Factor analysis has been conceptually available to researchers since the turn of the century (Spearman, 1904), but as a practical matter has been widely used only with the more recent availability of both modern computers and user-friendly statistical software packages. Factor analysis examines patterns of relationships among factored entities (often variables) across replicates (usually people), with a view toward creating clusters or factors of the factored entities.

Several matrices of association can be examined as the basis for the clustering process, including the variance-covariance matrix (e.g., Thompson & Borrello, 1987a), but many analysts employ a matrix of bivariate correlation coefficients for this purpose. Of course, even within the family of correlation coefficients, many choices are available. For example, Table 1 provides a comparison of the different data dynamics evaluated by the Pearson $\underline{r}$ and Spearman's rho. Dolenz-Walsh (1996) provides a comprehensive and readable explanation of the data features that do and do not influence various correlation coefficients.

INSERT TABLE 1 ABOUT HERE.

Typically, the matrix of associations is computed from a two-dimensional raw data matrix, e.g., rows representing scores of people, with the scores organized into columns representing the variables being measured. Analyses based on raw data matrices organized in this manner are termed *two-mode* factor analyses (Gorsuch, 1983, Chapter 15).

Although the most common two-mode analyses are based on data matrices with people defining rows, and variables defining columns, there are a number of two-mode analyses available to the researcher. Cattell (1966) conceptualized the possibilities as involving any combination of two dimensions (thus constituting a surface) from a "data box" defined by three dimensions: (a) variables, (b) participants (often people), and (c) occasions of measurement.

Table 2 presents the six "techniques" conceptualized and labelled by Cattell (1966), as well as illustrative applications of several of the techniques. Although all six techniques are available to researchers, R-technique (cf. Thompson & Borrello, 1992b) and Q-technique (cf. Thompson & Miller, 1984), respectively, are the most commonly applied analyses in contemporary practice.

INSERT TABLE 2 ABOUT HERE.

Since R-technique and Q-technique both involve the same two elements (i.e., variables and people, and occasion is held constant), both R and Q are from the same surface of Cattell's data box. But the raw data are organized differently to differentiate these two factor analytic methods.

It is the organization of the raw data matrix that distinguishes the six techniques, and not the mathematics of the factor analytic process. For example, if people define the rows of the raw data matrix, with variables defining the columns, the analysis is R-technique, regardless of how the factors are extracted (e.g., principal components, principal axis factoring, canonical factoring).

Thus, if the first person, Jennifer Loquacious, had scores of 1, 2, 3, 4 and 5 on five variables, respectively, the first *row* of the raw data matrix for an R-technique factor analysis would present scores of 1, 2, 3, 4, and 5 in a horizontal fashion, and the raw data matrix would have n rows of data, each with v=5 columns. So the raw data matrix would be an n x v matrix.

The same data could be *transposed* such that rows became columns and columns became rows. In this case, the first *column* of the raw data matrix would now present the scores of 1, 2, 3, 4, and 5, respectively. There were then be v=5 rows in the raw data matrix, and the matrix would have n columns. Figure 1 illustrates the transposition process.

INSERT FIGURE 1 ABOUT HERE.

Obviously, any raw data matrix can be transposed in the manner illustrated in Figure 1. This may (incorrectly) suggest that any single raw data matrix could be subjected to both R-technique (to factor variables) and Q-technique (to factor people) analyses.

The problem is that, whichever technique we apply, we generally want the number of row replicates to be several times larger than the number of the column entities that we are factoring. Thus, in R-technique we want several times more participants than factored variables, and in Q-technique we want several times more variables than factored people. This is to allow the patterns of relationships among the factored entities to be replicated over quite a number of rows in the raw data matrix, so that we can be sure that the estimated relationships are stable, and therefore that the factors we extract from the matrix of associations will themselves also be stable. Figure 2 illustrates that we always want the raw data matrix we are analyzing to have more rows than columns.

INSERT FIGURE 2 ABOUT HERE.

Questions Addressed by Q-technique Factor Analysis

Q-technique factor analysis is well suited to the more *intensive* study of a relatively *small number* of people. Q-technique isolates types (or prototypes) of people. In fact, we often are more interested in types of people than we are in clusters of variables.

For example, we often hear educators and psychologists talk about "Type A Personalities," "Workacholics," and "Introverts." Q-technique factor analysis is useful for (a) exploring data to identify new person types, and thus developing typological theories, or (b) collecting data to confirm or disconfirm existing theories about person types. R-technique is not directly useful for this purpose, even though many researchers incorrectly use R-technique methods to investigate questions about person types.

Excellent in-depth treatments of Q-technique factor analysis are available from Stephenson (1953), Kerlinger (1986, Chapter 32), and Gorsuch (1983). Carr (1992) provides an excellent short treatment. Campbell's (1996) treatment is more comprehensive, and is equally readable.

Q-technique factor analysis can be used to address three primary questions:

1. How many types (factors) of people are there?
2. Which people are most associated with each type (e.g., are the expected people most associated with the expected person factors?)?
3. Which variables were and were not useful in differentiating the various person types/factors?

Methodological Issues in Q-technique Studies

Three sorts of methodological issues must be resolved in any Q-technique study. First, who should be factored? Second, which variables should be measured to help define the person factors? And, third, what response format should be used for data collection (i.e., a Q-technique study may or may not use a conventional Q-sort task)?

Persons

Q-technique factor analysis directly tests typological premises. As Kerlinger (1986, p. 521) explained, in Q

> one tests theories on small sets of individuals carefully chosen for their "known" or presumed possession of some significant characteristic or characteristics. One explores unknown and unfamiliar areas and variables for their identity, their interrelations, and their functioning.

Thus, the people who are factored in Q-technique analysis must be carefully selected. The selection is all the more important, because the Q-technique researcher has inherently elected to study (intensively) a small group of people (since even the most diligent participants cannot be expected to respond to more than 100 to 150 variables, and the number of factored people is limited by the number of variables, as noted previously).

Usually distinct groups of people are factored. For example, Thompson and Miller (1984) sampled both school district administrators and program evaluators, to determine whether job classification was associated with person types as regards perceptions of program evaluation. Similarly, Gillaspy, Campbell and Thompson (1996) sampled two different kinds of counselors to compare the therapist person factors defined by different perceptions of what love is.

Variables

The variables in a Q-technique analysis can be variables of many kinds, e.g., statements responded to with respect to degree of agreement or disagreement, or photographs responded to as regards physical attractiveness. There are two major choices regarding the selection of variables. One choice (e.g., Thompson, 1980b) is to use variables that are themselves implicitly *structured* (Kerlinger, 1986). For example, if the participants responded to the 42 items on the Love Attitudes Scale (Hendrick & Hendrick, 1990), the responses would be structured, because the scale includes seven items measuring each of the six types of love posited by Lee (1973).

Alternatively, if the variables are presumed to be representative of a single population of items or variables, then the study would be considered *unstructured*. For example, if the participants responded to the 55 items on the Love Relationships Scale (Thompson & Borrello, 1987b), the responses would be presumed to be unstructured, because the scale was developed inductively without premises regarding an underlying structure (Thompson & Borrello, 1992a).

Response Format

Quasi-normal Q-sort. Though many response formats are candidates for the measurement protocols used to collect Q-study data (Daniel, 1989), most researchers employ a Q-sort (Kerlinger, 1986, Chapter 32) protocol in Q-technique studies. Q-sorts require all participants to each put stimuli (e.g., cards each listing a statement) into a predetermined number of categories, with *exactly* a predetermined number of items being placed in each category. Most commonly the predetermined numbers of categories that go into each category are created so as to yield a normal or a quasi-normal, symmetrical distribution of scores. Kerlinger (1986, p. 509) provides an illustrative example for a Q-sort involving 90 statements sorted as follows:

n items	3 +	4 +	7 +	10 +	13 +	16 +	13 +	10 +	7 +	4 +	3 = 90
Category	10	9	8	7	6	5	4	3	2	1	0

This response format yields data that are considered *ipsative* (Cattell, 1944), because the protocol invokes a forced-choice response format in which responses to one item inherently constrain the possible choices for subsequent items. Though ipsative data are not suitable for use in R-technique factor analysis (Thompson, Levitov & Miederhoff, 1982), ipsative data are quite useful in studying commonalities in *intra*individual differences, as in Q-technique factor analysis.

The Q-sort protocol is appealing, because the protocol yields data for each participant that are exactly equally distributed, i.e., data that for each participant are symmetrical, and have exactly the same skewness and kurtosis. As Glass and Hopkins (1984, p. 91) noted, "*r* can equal 1.0 only when the marginal distributions of *X* and *Y* have precisely the same shape." Thus, having data with exactly the same distributional shapes is appealing, because when we correlate the participants, none of the person correlation coefficients will be attenuated by differences in score distribution shapes, even if we are computing a matrix of Pearson *r* coefficients as the basis for the Q-technique factor analysis.

Mediated Q-sort. The Q-sort is appealing because the protocol allows participants to provide data regarding a lot of variables without being cognitively overwhelmed. For example, it is not reasonable to ask participants to rank-order more than 15 to 20 variables with no ties. The task of rank-ordering 90 items would irritate and confuse even the most patient and brightest participant.

However, Thompson (1980a) has proposed a *two-stage* measurement protocol that does yield data that are rank-ordered with no ties. First, participants complete a conventional Q-sort protocol. Second, participants are then asked to rank-order the statements within each of the Q-sort categories. This strategy yields more variance in responses, and so theoretically should allow isolation of more stable factors of participants.

Unnumbered graphic scale. *Normative* measurement (Cattell, 1944) allows participants to rate (as against rank) data, and the response to one item does not in any way mechanically constrain participants' responses to other items. With Likert scales, for example, the response to item one does not physically constrain my response to other items. The only constraints are self-imposed psychological (non-mechanical) constraints in the event that I elect to respond consistently to items containing roughly the same content.

What drives reliability of scores is having greater variance in our data (Reinhardt, 1996). Traditionally, there was considerable debate about whether it might be desirable in attitude measurement to employ a 1-7 Likert scale, as against a 1-5 scale, whether a 1-9 scale might be more preferable still, and so forth. Certainly, more response alternatives allow participants to provide more variable responses, if they wish to do so. As Nunnally (1967, p. 521) explained, "It is true that, as the number of scale points increases, the error variance increases, but at the same time, the true-score variance increases at an even more rapid rate." Thus, Guilford (1954, p. 291) suggested that "it may pay in some favorable situations to use up to 25 scale divisions."

Yet, as Thompson (1981, p. 5) noted, "use of a large number of scale steps... becomes undesirable when participants become confused or irritated at being confronted with a cognitively overwhelming number of response alternatives." Confused or irritated participants may not pay as much attention to rating tasks, and may therefore provide less reliable data.

However, Thompson (1981) described a response format that may reduce cognitive press on participants while still yielding normative data that are highly variable. This response format has been labelled an *unnumbered graphic scale*. Participants are presented with a straight line drawn between two antonyms (e.g., "Disagree" and "Agree") and are asked to draw a mark through the line at the position that best indicates the extent of their agreement with a given statement. These marks are subsequently scored by the researcher using an equal-interval measurement scaled with a relatively large number of categories, e.g., 1 to 15. This protocol puts a limited cognitive burden on participants, but can still yield more variable scores.

Of course, using normative data will mean that the bivariate correlation coefficients analyzed in a Q-technique factor analysis will inherently be attenuated by variations in the distribution shapes of scores for different individuals, and that these differences will affect the identification of the factors extracted from the correlations. The assumption that distributions of scores are the same across people is perfectly met with both Q-sort and mediated Q-sort measurement protocols, but will not be perfectly met with normative data.

However, it is conceivable that tolerating some deviations in distribution shapes will not devastate the factor analytic solution, and may be worthwhile if not requiring people to make forced choices yields more accurate reflections of their feelings. *It is ironic that we typically do not see much attention paid to the distributional requirements that also apply in R-technique factor analyses, while we seem to have obsessive concerns regarding the same dynamics in the Q-technique analyses that employ exactly the same mathematics.*

Illustrative Example

Table 3 presents an hypothetical heuristic data set that will be employed to illustrate the process of addressing the three questions typically posed in a Q-technique factor analysis. Under federal law both parents and teachers participate in formulating special education early intervention programs for children. However, it might be interesting to explore parent and teacher perceptions of these interventions, and whether these perceptions are congruent.

INSERT TABLE 3 ABOUT HERE.

The data set involves three hypothetical parents and two hypothetical early intervention teachers. The five participants hypothetically ranked 15 variables describing special education early intervention programs. We forego here the important issues of exactly how the participants and the variables were selected. And it should also be noted that the typical Q study would involve both more people and more variables. Appendix A presents the SPSS for Windows program used to analyze the data and to generate the remaining tables and figures reported here.

In the data set the five participants hypothetically ranked the 15 program intervention features from "1" (most important) to "15" (least important). The scaling of responses will subsequently become very important to the interpretation of the results, as we shall see momentarily. That is, the scaling direction is arbitrary, but whatever scaling direction we select must be considered as part of the interpretation process.

Table 4 presents the descriptive statistics for the data. Since the participants all ranked 15 items with no ties, the distributions are identical. In a Q-technique study using either Q-sort or mediated ranking data collection methods, correct data entry can be confirmed partly by examining the person means (here all 8.0) and person standard deviations (here all 4.47214) to insure that they are equal across persons.

INSERT TABLE 4 ABOUT HERE.

Table 4 also presents the correlation coefficients of the persons with each other. A quick perusal of this small 5x5 matrix would suggest that the data delineate two discrete person factors, one involving the three parents, and one involving the two teachers. Of course, with real data the correlation matrix would be larger, and the coefficients would be less homogeneous within groups and more heterogenous across groups, so the person factors would be less obvious from mere inspection of the bivariate correlation matrix. This is why we estimate the person factors empirically rather than through mere subjective examination of a large and ambiguous correlation matrix.

Table 5 presents the two person factors extracted from the Table 4 person correlation matrix. These results address the first research question, *"How many types (factors) of people are there?"*. Here the answer is, two.

INSERT TABLE 5 ABOUT HERE.

Because the factors were rotated orthogonally, and are therefore uncorrelated (see Gorsuch, 1983), these coefficients are called *pattern/structure coefficients* (Thompson & Daniel, 1996). Each pattern/structure coefficient represents the correlation of a given person with a given person factor. For example, as reported in Table 5, PARENT2 is most highly correlated with (most prototypic of) person Factor I (r_s = .97013).

Thus, the Table 5 results also address the second research question, *"Which people are most associated with each person factor?"*. The three parents define the first person factor, while the two teachers define the second person factor.

A very helpful graphic representation of the factors can also be developed by plotting the factor pattern/structure coefficients. This is illustrated for these data in Figure 3. Such visual representations of factor analytic results can be very useful in synthesizing and communicating results in a non-numeric fashion.

INSERT FIGURE 3 ABOUT HERE.

The third Q-technique research question is, *"Which variables were and were not useful in differentiating the various person* *types/factors?"*. This question is addressed by consulting the factor scores computed as part of the analysis. Each variable will have a factor score on each person factor. These factor scores are in z-score form (i.e., have a mean of 0 and a standard deviation and variance of 1.0).

The factor scores can be conceptualized as a prototypic ranking of the variables as regards the persons defining a given person factor. For example, Table 6 presents the sorted factor scores on person Factor I.

INSERT TABLE 6 ABOUT HERE.

It often is useful to invoke cutscores to interpret Q-technique factor scores, and often |1.0| is used for this purpose. Thus, for the Table 6 results, the five variables most useful for defining person Factor I were variables 1 (-1.53274), 2 (-1.31822), 13 (1.32326), 15 (1.38541), and 14 (1.47291).

Because the *smallest number* ("1") in the Table 3 ranking of the 15 program features reflected the most important feature, this means that the three parents most associated with person Factor I found *most important* the program features (*smallest factor scores*):

1 emphasis on long-term intervention goals (-1.53274), and

2 consideration of all family members' needs as regards intervention (-1.31822).

The three parents most associated with person Factor I found *least important* the program features (largest factor scores):

13 attractiveness of the intervention setting (1.32326),

15 practicality/logistics of interventions (1.38541), and

14 costs of interventions (1.47291).

Regarding the person factor defined by the two teachers, as reported in Table 7, the program features the teachers found *most important* were:

5 consideration of social cohesion within intervention setting (-1.62933),

7 emphasis on social skills as intervention goal (-1.60040), and

3 involvement of family members in providing assessment information (-1.04982).

The program features the teachers found *least important* were:

6 access of intervention re scheduling (1.00791),

1 emphasis on long-term intervention goals (1.20159), and

9 access of intervention re geographic location (1.72246).

INSERT TABLE 7 ABOUT HERE.

Another analysis can be conducted to isolate those variables that were most salient or relevant across the *set* of person factors, and which items were least salient across the set of person factors. This can be done by computing the average absolute value of the factors scores of a given variable across all the factors. Table 8 presents these results for the present data.

INSERT TABLE 8 ABOUT HERE.

For example, the program feature that was most salient across both person factors was the item:

1 emphasis on long-term intervention goals ([|-1.53274| +

|1.20159|] / 2 = 1.3672).

The item most irrelevant to defining the two person factors was the program feature:

10 use of technology in intervention (.4083).

Discussion

Q-technique factor analysis can be useful in education program evaluation and research projects, because the method addresses questions about *person types*, and educators and psychologists are often more interested in people than in variables. Too many researchers use R-technique factoring of variables in a vain attempt to address questions about types of people.

The heuristic example illustrates the potential application of Q-technique methods to address an evaluation/research question. In theory it might be hoped that parents and teachers who jointly participate in special education early interventions for children would be congruent in their valuing of various intervention features (i.e., agree which features are important or unimportant, and agree which features are essentially irrelevant). In the illustrative example, this expectation would be contradicted by a finding that two person-factors were identified, and the finding that the two uncorrelated person factors consisted on the one hand of parents and on the other of teachers. Figure 3 presents a graphic representation of this finding.

However, Q-technique factor analysis can also be employed to identify the basis for person factor differentiation. As reported in Table 6, parents most highly valued intervention features emphasizing long-term focus and consideration of the needs of the family as a unit, and least valued practical aspects of the intervention (i.e., intervention physical setting attractiveness, logistics, and costs). As reported in Table 7, teachers on the other hand, most valued social skills aspects of the intervention, and least valued longer-term intervention issues and intervention scheduling and location concerns. As reported in Table 8, both groups concurred that use of technology was a generally irrelevant program feature.

In usual applications Q-technique employs a response format that is ipsative, as noted previously. This analytic model is most useful in studying aspects of reality that are themselves inherently forced-choice. There may be myriad early intervention features that are desirable. But practical realities constrain the creation of an ideal program developed sans resource constraints, and so choices must be made.

In the heuristic example, the parents and the teachers might have *rated* all 15 (or all 75, or 150) program features as 10 on a 1-to-10 scale (with 10 ideal). But since programs cannot pursue all possible ends with all possible means, a data collection strategy that requires forced-choice *ranking* of program features honors a reality in which forced-choice is necessary at the implementation level. The Q-technique methods described here are well suited to studying education phenomena in which there are numerous ideals present in a reality in which only a limited number of ends or means can be realistically pursued.

References

Campbell, T. (1996). Investigating structures underlying relationships when variables are not the focus: Q-technique and other techniques. In B. Thompson (Ed.), Advances in social science methodology (Vol. 4, pp. 207-218). Greenwich, CT: JAI Press.

Carr, S. (1992). A primer on Q-technique factor analysis. Measurement and Evaluation in Counseling and Development, 25, 133-138.

Cattell, R.B. (1944). Psychological measurement: Normative, ipsative, interactive. Psychological Review, 51, 292-303.

Cattell, R.B. (1953). A quantitative analysis of the changes in the culture pattern of Great Britain, 1837-1937, by P-technique. Acta Psychologia, 9, 99-121.

Cattell, R.B. (1966). The data box: Its ordering of total resources in terms of possible relational systems. In R.B. Cattell (Ed.), Handbook of multivariate experimental psychology (pp. 67-128). Chicago: Rand McNally.

Daniel, L. G. (1989, November). Stability of Q-factors across two data collection methods. Paper presented at the annual meeting of the Mid-South Educational Research Association, Little Rock. (ERIC Document Reproduction Service No. ED 314 438)

Dolenz-Walsh, B. (1996). Factors that attenuate the correlation coefficient and its analogs. In B. Thompson (Ed.), Advances in social science methodology (Vol. 4, pp. 21-32). Greenwich, CT: JAI Press.

Frankiewicz, R.G., & Thompson, B. (1979, April). A comparison of strategies for measuring teacher brinkmanship behavior. Paper presented at the annual meeting of the American Educational Research Association, San Francisco. (ERIC Document Reproduction Service No. ED 171 753)

Gillaspy, A., Campbell, T., & Thompson, B. (1996, January). Types of lovers: A Q-technique factor analysis of counselor person-factors defined by counselors' love attitudes. Paper presented at the annual meeting of the Southwest Educational Research Association, New Orleans.

Glass, G.V, & Hopkins, K.D. (1984). Statistical methods in education and psychology (2nd ed.). Englewood Cliffs, NJ: Prentice-Hall.

Gorsuch, R.L. (1983). Factor analysis (2nd ed.). Hillsdale, NJ: Erlbaum.

Guilford, J.P. (1954). Psychometric methods. New York: McGraw-Hill.

Hendrick, C., & Hendrick, S.S. (1990). A relationship-specific version of the Love Attitudes Scale. Journal of Social Behavior and Personality, 5, 239-254.

Jones, H.L., Thompson, B., & Miller, A.H. (1980). How teachers perceive similarities and differences among various teaching models. Journal of Research in Science Teaching, 17, 321-326.

Kerlinger, F.N. (1986). Foundations of behavioral research (3rd ed.) New York: Holt, Rinehart and Winston.

Lee, J. A. (1973). The colors of love: An exploration of the ways of loving. Don Mills, Ontario: New Press. (Popular Edition, 1976)

Nunnally, J.C. (1967). Psychometric theory. New York: McGraw-Hill.

Reinhardt, B. (1996). Factors affecting coefficient alpha: A mini Monte Carlo study. In B. Thompson (Ed.), Advances in social science methodology (Vol. 4, pp. 3-20). Greenwich, CT: JAI Press.

Spearman, C. (1904). "General intelligence," objectively determined and measured. American Journal of Psychology, 15, 201-293.

Stephenson, W. (1953). The study of behavior: Q-technique and its methodology. Chicago: The University of Chicago Press.

Thompson, B. (1980a). Comparison of two strategies for collecting Q-sort data. Psychological Reports, 47, 547-551.

Thompson, B. (1980b). Validity of an evaluator typology. Educational Evaluation and Policy Analysis, 2, 59-65.

Thompson, B. (1981, January). Factor stability as a function of item variance. Paper presented at the annual meeting of the Southwest Educational Research Association, Dallas. (ERIC Document Reproduction Service No. ED 205 553)

Thompson, B., & Borrello, G. M. (1987a, January). Comparisons of factors extracted from the correlation matrix versus the covariance matrix: An example using the Love Relationships Scale. Paper presented at the annual meeting of the Southwest Educational Research Association, Dallas. (ERIC Document Reproduction Service No. ED 280 862)

Thompson, B., & Borrello, G. (1987b). Concurrent validity of a love relationships scale. Educational and Psychological

Measurement, 47, 985-995.

Thompson, B., & Borrello, G. (1992a). Different views of love: Deductive and inductive lines of inquiry. Current Directions in Psychological Science, 1, 154-156.

Thompson, B., & Borrello, G.M. (1992b). Measuring second-order factors using confirmatory methods: An illustration with the Hendrick-Hendrick love instrument. Educational and Psychological Measurement, 52, 69-77.

Thompson, B., & Daniel, L.G. (1996). Factor analytic evidence for the construct validity of scores: An historical overview and some guidelines. Educational and Psychological Measurement, 56, 213-224.

Thompson, B., Levitov, J.E., & Miederhoff, P.A. (1982). Validity of the Rokeach Value Survey. Educational and Psychological Measurement, 42, 899-905.

Thompson, B., & Miller, L. A. (1984). Administrators' and evaluators' perceptions of evaluation. Educational and Psychological Research, 4, 207-219.

Table 1
Hypothetical Data Illustrating What Factors Influence the Pearson r and Spearman's rho

r asks: *Do the two variables order the people in the same order and do the two variables have the same shape?*

rho asks only: *Do the two variables order the people in the same order?*

Data Set #1

X	Y	Person
1	1	James D. Bowwana
2	2	Becca Broker
3	3	Patricia Ferragamo
4	4	Marcia "Willie" Schumaker

Do the two variables order the people in the same order and do the two variables have the same shape? **Yes, therefore r = +1.**
Do the two variables order the people in the same order? **Yes, therefore rho = +1.**

Data Set #2

X	Y	Person
1	2	James D. Bowwana
2	3	Becca Broker
3	4	Patricia Ferragamo
4	5	Marcia "Willie" Schumaker

Do the two variables order the people in the same order and do the two variables have the same shape? **Yes, therefore r = +1.**
Do the two variables order the people in the same order? **Yes, therefore rho = +1.**
Note. Additive constants do not affect correlation coefficients.

Data Set #3

X	Y	Person
1	2	James D. Bowwana
2	4	Becca Broker
3	5	Patricia Ferragamo
4	8	Marcia "Willie" Schumaker

Do the two variables order the people in the same order and do the two variables have the same shape? **Yes, therefore r = +1.**
Do the two variables order the people in the same order? **Yes, therefore rho = +1.**
Note. Multiplicative constants do not affect correlation coefficients.

<u>Data Set #4</u>

X	Y	Person
1	1	James D. Bowwana
2	2	Becca Broker
3	3	Patricia Ferragamo
4	999	Marcia "Willie" Schumaker

Do the two variables order the people in the same order <u>*and*</u> *do the two variables have the same shape?* **No, therefore $\underline{r} \neq +1$.**

Do the two variables order the people in the same order? **Yes, therefore rho = +1.**

Note. Here the two variables order the 4 people in exactly the same order. However, the shapes of the two distributions are different. The <u>X</u> scores are "rectangular" (also called "uniform") and symmetrical (not skewed), while the <u>Y</u> scores are non-symmetrical (positively skewed).

Table 2
Six Variations of Two-Mode Factor Analysis

Technique Label	Columns Defining Entities to be Factored	Rows Defining the Patterns of Associations	Example Application
R	Variables	Participants	Thompson & Borrello (1987b)
Q	Participants	Variables	Thompson (1980b)
O	Occasions	Variables	Jones, Thompson & Miller (1980)
P	Variables	Occasions	Cattell (1953)
T	Occasions	Participants	Frankiewicz & Thompson (1979)
S	Participants	Occasions	

Table 3
Illustrative Data for Q-technique Intervention Study

Parents			Teachers		
1	2	3	1	2	Intervention Feature
1	2	1	13	13	1 emphasis on long-term intervention goals
2	1	4	7	7	2 consideration of all family members' needs as regards intervention design
3	9	6	5	3	3 involvement of family members in providing assessment information
4	3	5	6	6	4 participation of other family members in intervention
5	7	7	2	1	5 consideration of social cohesion within intervention setting
6	5	3	12	12	6 access of intervention re scheduling
7	6	8	1	2	7 emphasis on social skills as intervention goal
8	4	2	10	10	8 quantity of intervention personnel per child
9	8	9	15	15	9 access of intervention re geographic location
10	11	10	4	14	10 use of technology in intervention
11	10	11	14	4	11 formal education of intervention personnel
12	12	12	8	8	12 having a manageable number of intervention goals
13	13	15	11	11	13 attractiveness of the intervention setting
14	15	14	9	9	14 costs of interventions
15	14	13	3	5	15 practicality/logistics of interventions

Table 4
Descriptive Statistics and NxN *r* Matrix for Q-technique Data
(Abridged from Output Generated Using the Appendix A Program)

	Mean	Std Dev	Label
PARENT1	8.00000	4.47214	
PARENT2	8.00000	4.47214	
PARENT3	8.00000	4.47214	
TEACHER1	8.00000	4.47214	
TEACHER2	8.00000	4.47214	

Number of Cases = 15

Correlation Matrix:

	PARENT1	PARENT2	PARENT3	TEACHER1	TEACHER2
PARENT1	1.00000				
PARENT2	.88214	1.00000			
PARENT3	.87143	.92143	1.00000		
TEACHER1	.05000	-.08571	-.09286	1.00000	
TEACHER2	.10714	-.01786	-.07500	.62500	1.00000

Table 5
NxF Varimax-rotated Pattern/Structure Coefficient Matrix
(Abridged from Output Generated Using the Appendix A Program)

Rotated Factor Matrix:

	Factor 1	Factor 2
PARENT1	.95385	.10629
PARENT2	.97013	-.04987
PARENT3	.96537	-.08778
TEACHER1	-.03857	.89935
TEACHER2	.01859	.90247

Table 6
Sorted Factor Scores on *Factor I* from the VxF Factor Score Matrix
(Abridged from Output Generated Using the Appendix A Program)

	FSCORE1	FEATURE
1	-1.53274	1 emphasis on long-term intervention goals
2	-1.31822	2 consideration of all family members' needs as regards intervention
3	-.93422	4 participation of other family members in intervention
4	-.76982	8 quantity of intervention personnel per child
5	-.76290	6 access of intervention re scheduling
6	-.47698	3 involvement of family members in providing assessment information
7	-.40611	5 consideration of social cohesion within intervention setting
8	-.24820	7 emphasis on social skills as intervention goal
9	.17359	9 access of intervention re geographic location
10	.56769	10 use of technology in intervention
11	.59811	11 formal education of intervention personnel
12	.92822	12 having a manageable number of intervention goals
13	1.32326	13 attractiveness of the intervention setting
14	1.38541	15 practicality/logistics of interventions
15	1.47291	14 costs of interventions

Table 7
Sorted Factor Scores on *Factor II* from the VxF Factor Score Matrix
(Abridged from Output Generated Using the Appendix A Program)

	FSCORE2	FEATURE	
1	-1.62933	5	consideration of social cohesion within intervention setting
2	-1.60040	7	emphasis on social skills as intervention goal
3	-1.04982	3	involvement of family members in providing assessment information
4	-.93679	15	practicality/logistics of interventions
5	-.50621	4	participation of other family members in intervention
6	-.27625	2	consideration of all family members' needs as regards intervention
7	.01096	12	having a manageable number of intervention goals
8	.24891	10	use of technology in intervention
9	.25488	11	formal education of intervention personnel
10	.25705	14	costs of interventions
11	.56540	8	quantity of intervention personnel per child
12	.72963	13	attractiveness of the intervention setting
13	1.00791	6	access of intervention re scheduling
14	1.20159	1	emphasis on long-term intervention goals
15	1.72246	9	access of intervention re geographic location

Table 8
Sorted Average Absolute Values
of Factor Scores from the VxF Factor Score Matrix
(Abridged from Output Generated Using the Appendix A Program)

	ABSFSAVG	FEATURE	
1	1.3672	1	emphasis on long-term intervention goals
2	1.1611	15	practicality/logistics of interventions
3	1.0264	13	attractiveness of the intervention setting
4	1.0177	5	consideration of social cohesion within intervention setting
5	.9480	9	access of intervention re geographic location
6	.9243	7	emphasis on social skills as intervention goal
7	.8854	6	access of intervention re scheduling
8	.8650	14	costs of interventions
9	.7972	2	consideration of all family members' needs as regards intervention
10	.7634	3	involvement of family members in providing assessment information
11	.7202	4	participation of other family members in intervention
12	.6676	8	quantity of intervention personnel per child
13	.4696	12	having a manageable number of intervention goals
14	.4265	11	formal education of intervention personnel
15	.4083	10	use of technology in intervention

Figure 1
Illustration of Data Matrix Transposition in **R** versus **Q** Studies

R-technique Raw Data Matrix

Person	Variable V1	V2	V3	V4	V5
Jennifer Loquacious (JL)	1	2	3	4	5
Person #2	6	7	8	9	10
Person #3	11	12	13	14	15
Person #4	16	17	18	19	20

Note. The raw data matrix here is n=4 persons by v=5 variables (i.e., 4 x 5).

Q-technique Raw Data Matrix

Variable	Person JL	#2	#3	#4
V1	1	6	11	16
V2	2	7	12	17
V3	3	8	13	18
V4	4	9	14	19
V5	5	10	15	20

Note. The raw data matrix here is v=5 variables by n=4 persons (i.e., 5 x 4).

Figure 2
Two Two-Mode (**R** and **Q**) Variations
from One of the Three Faces of Cattell's Data Box

$$\begin{array}{cc} & \begin{array}{cccc} 1 & 2 & \dots & v \end{array} \\ \begin{array}{c} 1 \\ 2 \\ \dots \\ \\ n \end{array} & \left[\begin{array}{cccc} & & & \\ \\ \\ \\ \\ \end{array}\right] \end{array}$$

<u>Note</u>. In the raw data matrix used for **R**-technique factor analysis, each of the <u>n</u> *persons* defines a *row* of data, and each set of scores of the people on each of the <u>v</u> *variables* defines a *column* of data.

$$\begin{array}{cc} & \begin{array}{cccc} 1 & 2 & \dots & n \end{array} \\ \begin{array}{c} 1 \\ 2 \\ \dots \\ \\ v \end{array} & \left[\begin{array}{cccc} & & & \\ \\ \\ \\ \\ \end{array}\right] \end{array}$$

<u>Note</u>. In the raw data matrix used for **Q**-technique factor analysis, each set of scores of the people on each of the <u>v</u> *variables* defines a *row* of data, and each of the <u>n</u> *persons* defines a *column* of data.

Figure 3
Five Persons Arrayed in the Person Factor Space

```
               Factor II
                  I
                4 5
                  I
                  I
                  I
                  I
                  I
                  I
                  I
                  I
                  I
                  I
                  I
                  I
                  I
                  I                                1
                  I
- - - - - - - - - + - - - - - - - - - - - - - - - - -   I
                  I                                2
                  I                                3
                  I
                  I
                  I
                  I
                  I
                  I
                  I
                  I
                  I
                  I
                  I
                  I
                  I
                  I
                  I
```

<u>Note</u>. "1" = PARENT1; "2" = PARENT2; "3" = PARENT3; "4" = TEACHER1; "5" = TEACHER2.

APPENDIX A
SPSS Program to Analyze the Table 1 Q-technique Data

```
SET BLANKS=SYSMIS UNDEFINED=WARN printback=listing.
TITLE 'CRIEI Heuristic Q-technique Data ********************'.
DATA LIST
  FILE='c:\spsswin\qtech.dta' FIXED RECORDS=1 TABLE
  /1 parent1 1-2 parent2 5-6 parent3 9-10
     teacher1 13-14 teacher2 17-18 feature (3X,A69) .
list variables=all/cases=99/format=numbered .
SUBTITLE '1  FACTOR 3 Parents and 2 Teachers ###############'.
EXECUTE.
FACTOR VARIABLES=parent1 to teacher2/
  PRINT=ALL/PLOT=ROTATION(1,2)/
  CRITERIA=ITERATE(99)/EXTRACTION=PC/ROTATION=VARIMAX/
  SAVE=REG(ALL FSCORE).
subtitle '2a  Discriminating Scores on Person Factor I $$$$$'.
execute .
sort cases by fscore1 .
list variables=fscore1 feature/cases=99/format=numbered .
subtitle '2b  Discriminating Scores on Person Factor II $$$$'.
execute .
sort cases by fscore2 .
list variables=fscore2 feature/cases=99/format=numbered .
subtitle '2c  Average Features Factor Scores ###############'.
execute .
compute absfsavg=(abs(fscore1) + abs(fscore2)) / 2. .
print formats absfsavg (F8.4) .
sort cases by absfsavg (D) .
list variables=absfsavg feature/cases=99/format=numbered .
```

U.S. DEPARTMENT OF EDUCATION
Office of Educational Research and Improvement (OERI)
Educational Resources Information Center (ERIC)

REPRODUCTION RELEASE

(Specific Document)

TM028951

I. DOCUMENT IDENTIFICATION:

Title: USING Q-TECHNIQUE FACTOR ANALYSIS IN EDUCATION PROGRAM EVALUATIONS AND RESEARCH: AN INTRODUCTORY PRIMER

Author(s): BRUCE THOMPSON

Corporate Source:

Publication Date: 5/2/98

II. REPRODUCTION RELEASE:

In order to disseminate as widely as possible timely and significant materials of interest to the educational community, documents announced in the monthly abstract journal of the ERIC system, *Resources in Education* (RIE), are usually made available to users in microfiche, reproduced paper copy, and electronic/optical media, and sold through the ERIC Document Reproduction Service (EDRS) or other ERIC vendors. Credit is given to the source of each document, and, if reproduction release is granted, one of the following notices is affixed to the document.

If permission is granted to reproduce the identified document, please CHECK ONE of the following options and sign the release below.

[X] ← Sample sticker to be affixed to document

Check here

Permitting microfiche (4"x 6" film), paper copy, electronic, and optical media reproduction

"PERMISSION TO REPRODUCE THIS MATERIAL HAS BEEN GRANTED BY

BRUCE THOMPSON

TO THE EDUCATIONAL RESOURCES INFORMATION CENTER (ERIC)."

Level 1

Sample sticker to be affixed to document → [ ]

or here

Permitting reproduction in other than paper copy.

"PERMISSION TO REPRODUCE THIS MATERIAL IN OTHER THAN PAPER COPY HAS BEEN GRANTED BY

Sample

TO THE EDUCATIONAL RESOURCES INFORMATION CENTER (ERIC)."

Level 2

Sign Here, Please

Documents will be processed as indicated provided reproduction quality permits. If permission to reproduce is granted, but neither box is checked, documents will be processed at Level 1.

"I hereby grant to the Educational Resources Information Center (ERIC) nonexclusive permission to reproduce this document as indicated above. Reproduction from the ERIC microfiche or electronic/optical media by persons other than ERIC employees and its system contractors requires permission from the copyright holder. Exception is made for non-profit reproduction by libraries and other service agencies to satisfy information needs of educators in response to discrete inquiries."

Signature:	Position: PROFESSOR
Printed Name: BRUCE THOMPSON	Organization: TEXAS A&M UNIVERSITY
Address: TAMU DEPT EDUC PSYC COLLEGE STATION, TX 77843-4225	Telephone Number: (409) 845-1335
	Date: 4/24/98